



COMMUNICATION *un*BREAKDOWN



Finding Targets for Earnest Conversation and Its Application to Voting



Katie



Nick



Dani



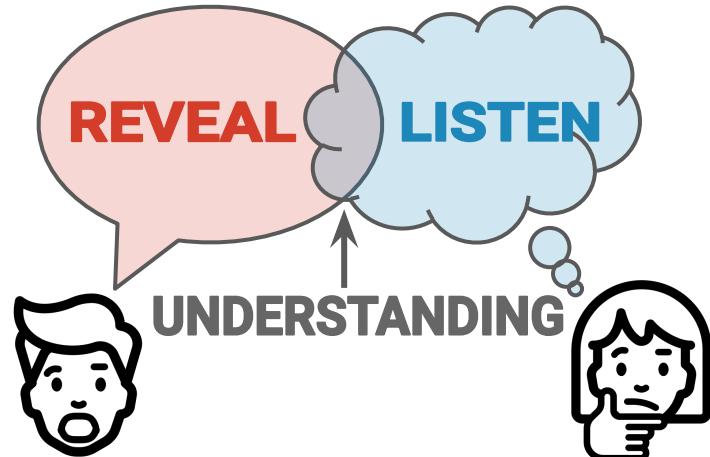
Kevin

Image created in Adobe Illustrator under the tutelage of [Andrei Stefan](#)
Communication Breakdown song by [Led Zeppelin](#)

People's Action is changing hearts and minds one conversation at a time.

**PEOPLE'S
ACTION**

DEEP CANVASSING



Deep Canvassing is unique in how much listening is involved.



Traditional Canvass



Canvasser hurriedly reads from a script



Canvasser delivers a "message"



Usually under 30 seconds



Canvassers tell voters what to think



Deep Canvass



Voter does more talking than canvasser



Voter candidly describes personal experiences



Upwards of 30-60 minutes



Voters draw own conclusions

It is becoming increasingly difficult and more expensive to reach target voters.



The Plan

8M phone calls



The Challenge

3.1% change opinion

24K volunteers

\$14.72 per conversation

8 states

\$475 per change in
opinion



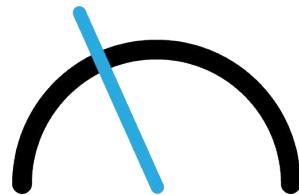
The Opportunity

↑ Improve conflicted voter targeting

↑ Increase number of positive conversations

People's Action connected with 33% more voters using our machine-learning informed method.

33%



Increase in Target Voters

Data + People = Power

"We paired this breakthrough form of organizing with cutting-edge data science, **using a machine-learning-informed method** that lets us improve our ability to find conflicted voters in real time." *



*From People's Action website
<https://peoplesaction.org/peoples-action-2020/>

We delivered our solution by defining a process,
creating an MVP, and deploying our models.



The Process



The MVP

$$f(x_i)$$

The Models

Deep Canvassing is about sharing stories.

Volunteer calls voter

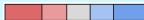
1

Hello!
May I
speak with
_____?

Volunteer makes contact with voter

2

When you think about your upcoming vote, where would you put yourself at this point?



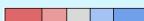
Voter offers who they plan to vote for

3

Do you have any concerns about the candidate?

5

Thank you for sharing! Where would you put yourself at this point?



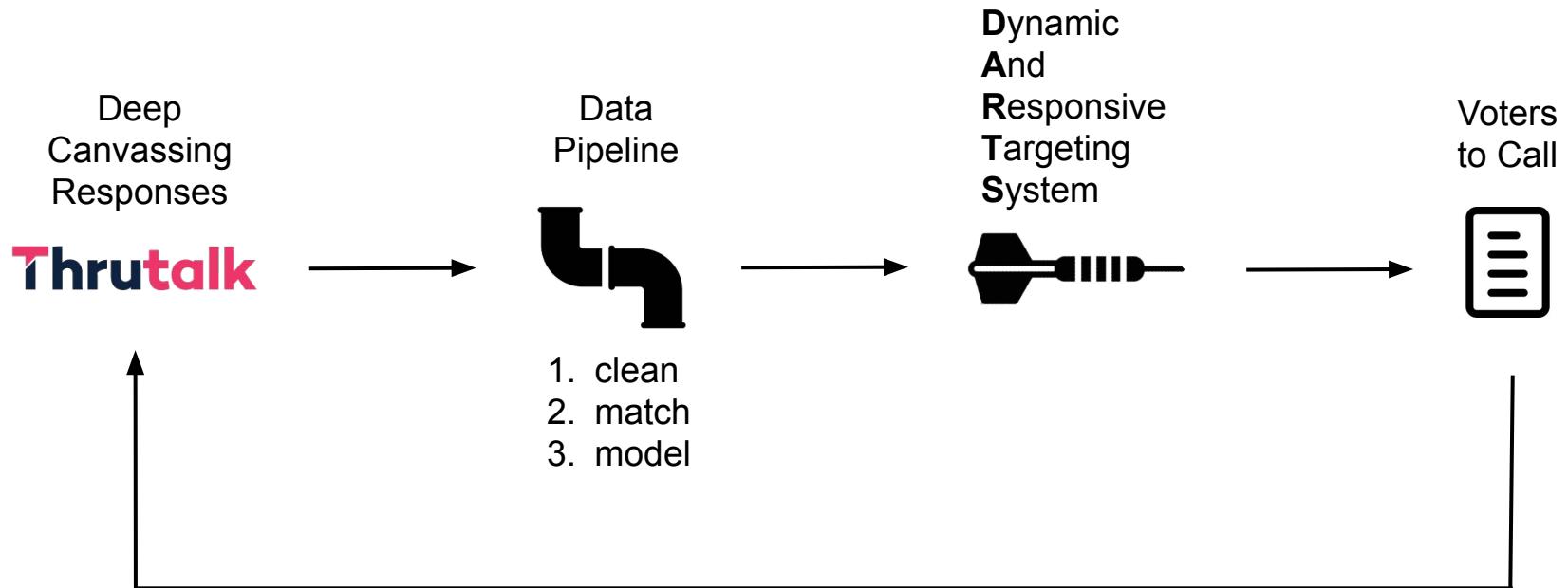
Volume of data

Voter and volunteer candidly share their stories with each other

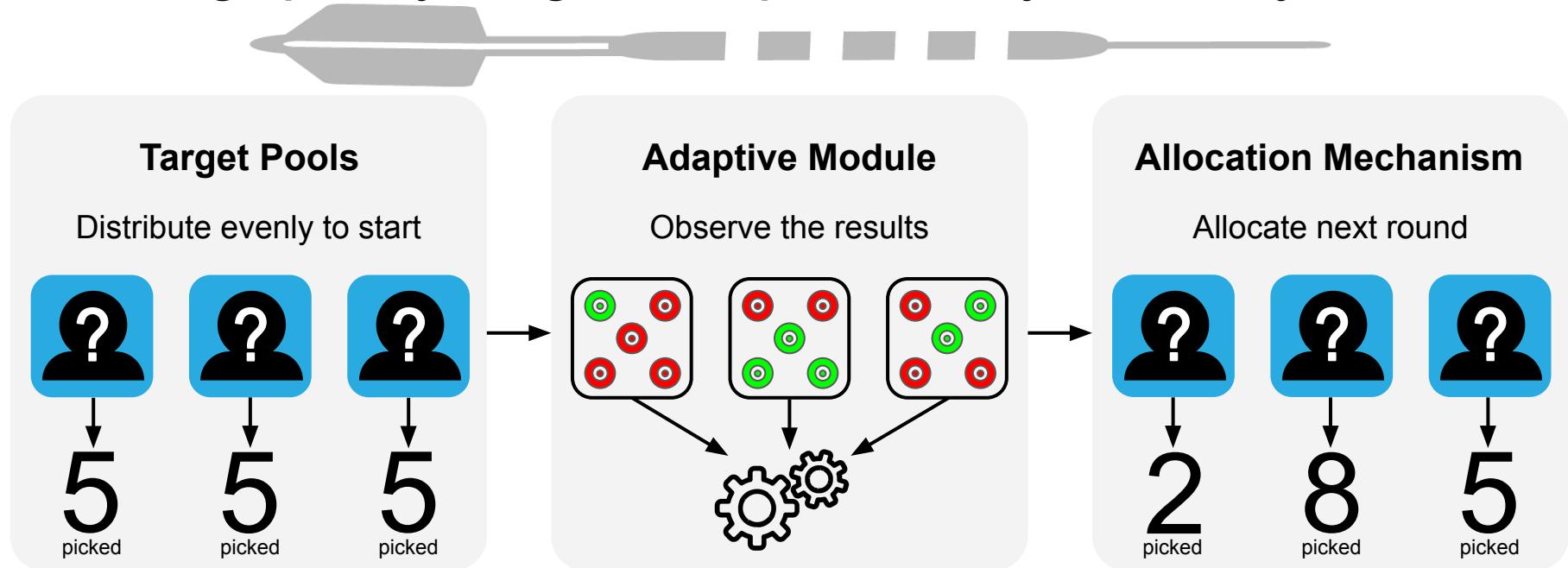
4

Voter offers who they plan to vote for, if changed

We identify targets through an active feedback loop.



Finding quality targets requires a dynamic system.



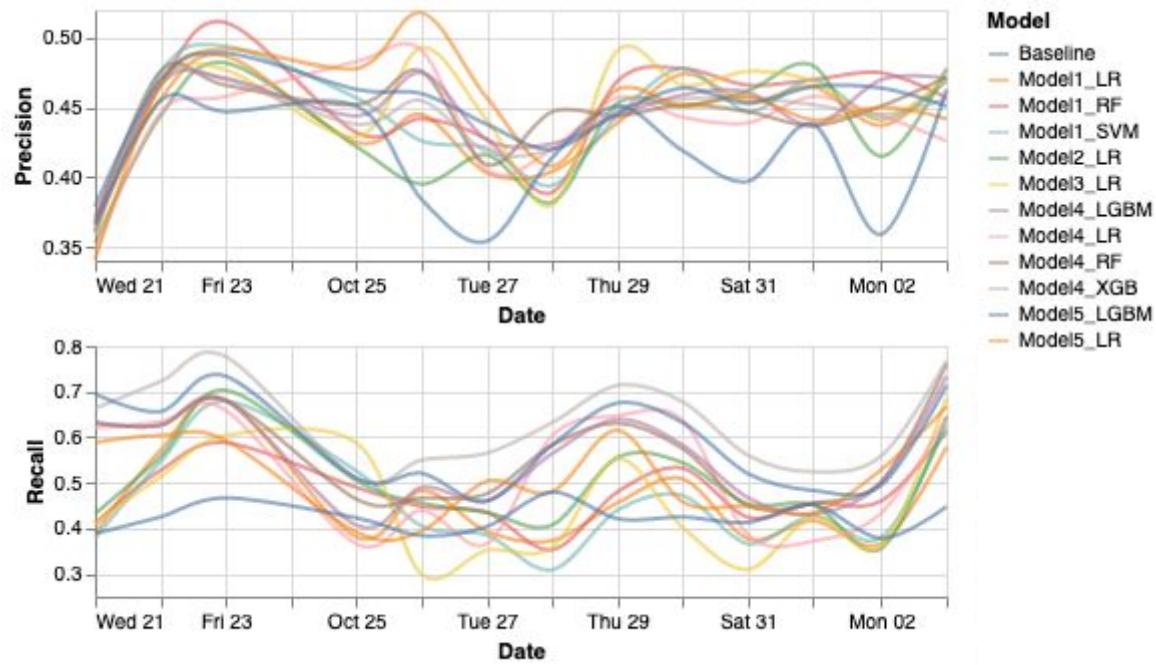
- Targets share attributes
- Unknown, dynamic distribution
- Flexible implementation

- Adapts from history
- Dictates next round
- Multi-armed Bandit

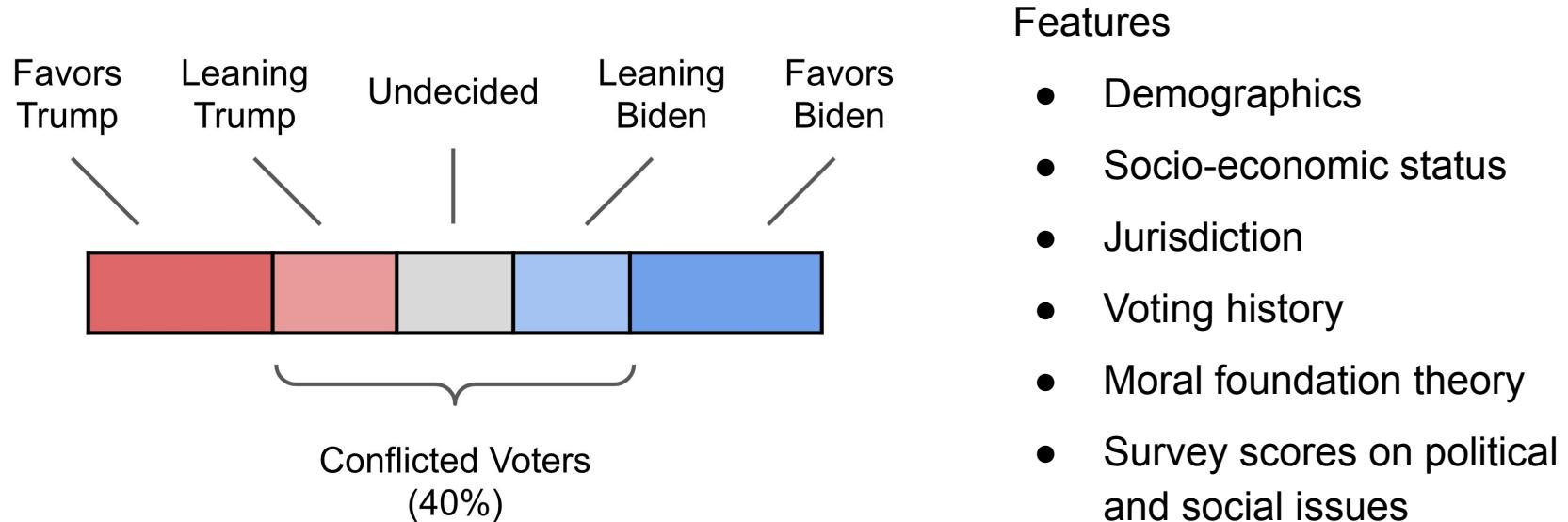
- Adaptive Module as input
- Picking strategy
- Domain dependent

In dynamic domains, concept drift becomes concept shift.

- Rapid concept drift:
 - Shifts in political climate
 - Noisy data
 - Human psychology
- MVP developed to account for:
 - Benefits of model diversification
 - Unforeseen uncertainty
 - Better predictive strategy

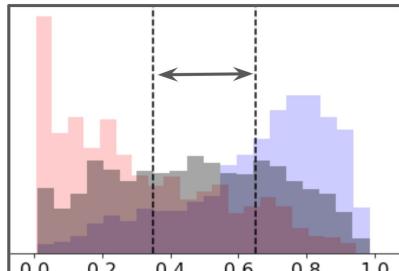


We trained our models on live campaign data.



We diversified our options by pursuing four strategies.

Strategy 1

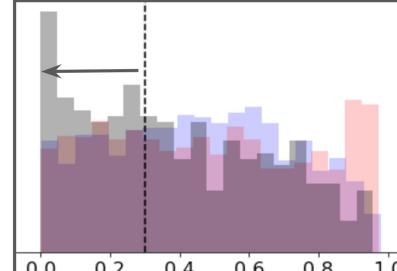


Target mid-range probabilities \longleftrightarrow

Training labels
Class 1 0 0 1 1

Uncertain binary classification model

Strategy 2

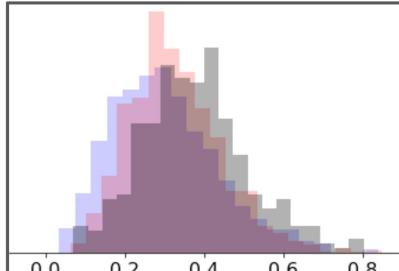


Target low difference in probabilities \longleftrightarrow

Training labels
Class 1 0 0 0 1 1
Class 2 1 1 0 0 0

Difference between two binary classification models

Strategy 3

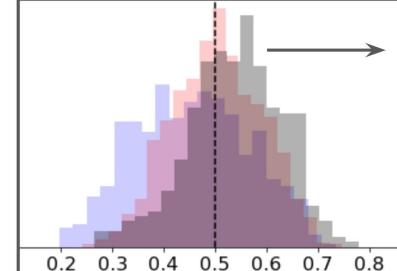


Target undecided class

Training labels
Class 1 0 0 1 2 2

Multi-class classification model

Strategy 4



Target high probabilities \longrightarrow

Training labels
Class 1 0 1 1 1 0

Single binary classification model

We trained our models on a variety of algorithms.

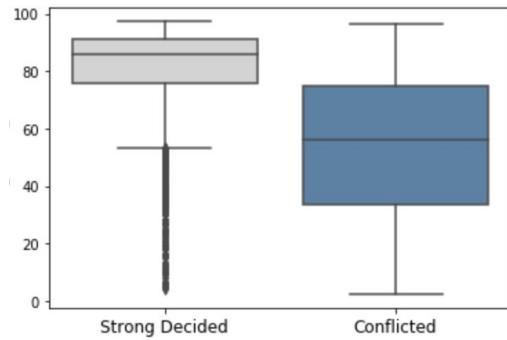
Algorithm	Strategy	Pros	Cons
Logistic Regression	1, 2, 3, 4	Generalizes well for a variety of classification problems, even with imbalanced classes; high explainability	May underperform if features are highly correlated/not linear
Random Forest	1, 4	Builds trees iteratively using features as split points; avoids overfitting through bagging; high explainability	Underperforms with imbalanced classes
SVM	1	Effective in high-dimensional space; good explainability	Slow to implement; may underperform depending on kernel function
KNN	1, 4	Tends to fit training data very well; difficult to explain	Overfits and does not generalize well
AdaBoost	4	Increases weights on observations that are difficult to predict in each iteration; performs well with imbalanced data; high explainability	Tends to underperform with high degree of noise in the data
XGBoost	1, 4	Efficient boosted decision trees classifier; generalizes well; high explainability	Underperforms with imbalanced classes
LightGBM	4	Very fast execution of boosted decision trees classifier; generalizes well; high explainability; better with Boruta	Underperforms with imbalanced classes

Recall was an important metric for evaluation.

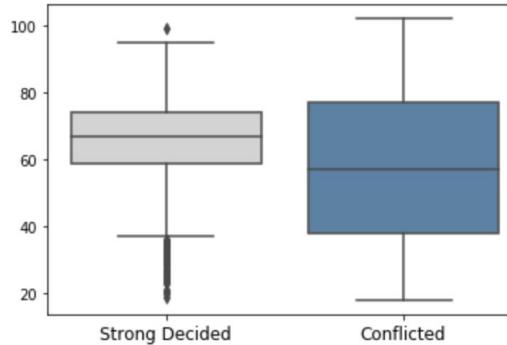
Strategy / Algorithm	Recall	Precision	Top 3 Features
Baseline: Logistic Regression	42%	41%	N/A
Strategy 1: Random Forest	46%	46%	Immigration Sentiment, Gun License, DACA Sentiment
Strategy 2: Logistic Regression	48%	45%	Immigration Sentiment, Gun License, Age
Strategy 3: Logistic Regression	42%	47%	Age, Sanctuary City Sentiment, Children Present
Strategy 4: Light GBM	60%	50%	Election Turnout, Tea Party, Affirmative Action Sentiment

Model explainability was important for our stakeholder.

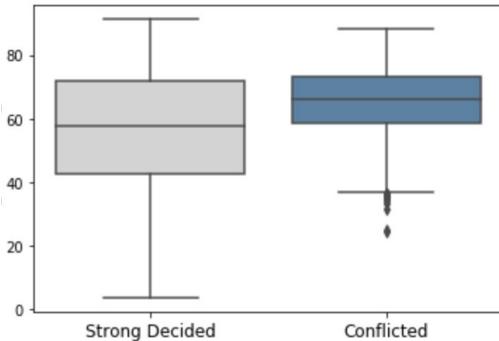
Election Turnout score
for Strategy 4
XGBoost



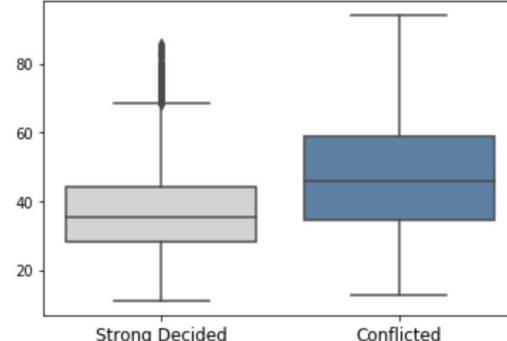
Age
for Strategy 4
XGBoost



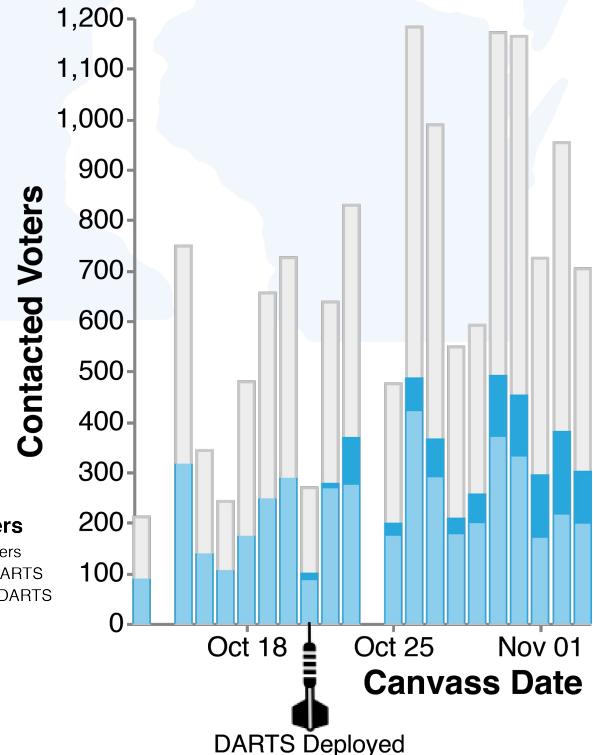
Immigration score
for Strategy 3
Logistic Regression



Universalism score
for Strategy 4
LightGBM



DARTS improved targeting for People's Action by 33%.



Key Learnings

- ★ Mission is impactful
- ▢ Deep Canvassing is challenging
- ⚙️ Matching voter demographic data is not straightforward
- ⟳ Active feedback loop from the campaign requires intensive data collaboration
- 🎯 DARTS is an effective way to solve similar problems

Our work can be applied to other big problems.

- Finding conflicted voters for state elections
- Finding conflicted people about vaccines
- Finding volunteers, change agents and donors



To find out more:

Install our software



<https://pypi.org/project/darts-berkeley/>

Fork us on Github



<https://github.com/Berkeley-Data/darts>

Visit our website



<https://unbreak.info>



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THANK YOU